R&D lab location. Evidence from the French case

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Version : april 2006

Abstract:

The purpose of this paper is to empirically investigate how regional advantages and firms characteristics influence the location of R&D. Looking at 2024 decisions of R&D lab location in France, we implement an extended conditional logit with spatially lagged explanatory variables to evaluate the importance of each factor and to test the spatial dimension of knowledge spillovers. The results indicate that large market size, large amount of ideas, and low level of competition in the target region increases the probability of setting up R&D labs while the diffusion of knowledge across regions induces a significant spatial dependence.

Keywords : Economic geography, Location choice, Knowledge spillovers, Spatial dependence

1. Introduction

Reductions in transportation and communication costs make it easier for firm to separate their production from their other activities (headquarter, management facilities, R&D laboratories, etc.). Duranton and Puga (2005) observe that this transformation modifies urban structure, cities shifting from a sectoral to a functional specialization. Then, an essential issue for regional development is to better understand the mechanisms underlying the location choice of these different kinds of activities and their consequences for the economic dynamics.

In this perspective, the main question that is at stake when considering this transformation, together with the emergence of a knowledge-based economy, is the location of R&D. Research activities are one of the driving forces behind economic growth on the one hand, and constitute one of the key assets of developed countries within the current re-engineering of international specializations on the other hand.

Recent theoretical literature focuses on this point, based on both economic geography models and endogenous growth theory[1]. In these 'geography and growth' models, public knowledge diffusion explains both the high geographic concentration of innovation activities and its consequences on economic growth (see Balwin et al. 2003 or Baldwin and Martin, 2005 for a review). The innovative sector is subject to a specific agglomeration force: the level of knowledge production characterising each region. Indeed, new knowledge produced by innovative firms is only partly appropriated. This public knowledge generates spillovers that reduce cost in the innovative sector. Thus, the location choice of innovative firms is driven by the innovation cost reduction induced by the amount of externalities available in each region.

[1] Englman and Walz (1995), Walz (1996), Baldwin and Forslid (2001), Martin and Ottaviano (1999), (2001), Baldwin, Martin and Ottaviano (2000).

However, the strength of this agglomeration force, and its effect on the growth rate, depend on the extent to which spillovers are localized. If there is no geographical constraint to public knowledge diffusion, firms in the innovative sector benefit from the same amount of spillovers whatever their location. Then geography does not impact the long term growth rate. Therefore, in these models, the hypothesis of a local dimension of spillovers is essential to account for the interrelations between two well-known stylized facts: the geographical concentration of innovation and the leading role of innovation in the growth process.

Several studies in the last fifteen years gave empirical evidence of such local spillovers[2]. (See Autant-Bernard and Massard, 2003 or Feldman and Audretsch, 2004 for review). However, they rely on aggregated data, whereas 'geography and growth' models are based on individual rational choices. The knowledge production function used is most of these studies relates the aggregated output of innovation in an area (county, metropolitan area, European region, etc.) to its aggregated R&D inputs. A more direct study of the decision process underlying firms location choice concerning innovative activities is still missing.

This location decision process is addressed in the studies of multinational firms location (see for instance Head and Mayer, 2003 ; Devereux, Griffith and Simpson 2003 ; Crozet, Mayer, Mucchielli, 2003) [3]. However, these works study firms as a whole, no matter what the type of activity in the studied unit may be. To our knowledge, however, there is no such attempt to assess the determinants of research activity location[4].

This paper suggests to study the determinants of R&D lab location, looking at 2,024 decisions of location in France from 1,689 firms. A conditional logit is implemented to evaluate the relative

[2] Jaffe (1989), Jaffe, Trajtenberg and Henderson (1993), Feldman (1994), Anselin,Varga and Acs (1997), Autant-Bernard (2001), Bottazzi and Peri (2003), Breshi and Lissoni (2003).
[3] See Mayer and Mucchielli (2004) for a review.
[4] The assessment carried out by Kenney and Florida (1994) based on interviews with Japanese biotechnology firms should be mentioned, however.

importance of the main factors governing the choice of a location. A spatial dependence process is introduced to estimate the spatial diffusion of knowledge spillovers.

This improves previous studies in two ways. First, it avoids the aggregation bias encountered in the 'geography of innovation' approach. Indeed, a major problem in most studies in this field comes from the geographical level of observation. The unit is the metropolitan area or county for the United States and the region (NUTS 2 or 3) in Europe. By focusing on an aggregated level, these studies are constrained by the administrative segmentation of a geographical scale which is often quite large and fail to quantify the spillovers enjoyed by each of these firms. They are measuring inter-agglomeration spillovers, whereas the major facts lie undoubtedly in the relationship between the firm and the agglomeration it belongs to (Lucas, 1988).
Second, in previous studies, knowledge spillovers are not estimated relatively to other agglomeration forces. While they account for non-market interactions, the studies of the 'geography of innovation' neglect the more traditional determinants of concentration. Consequently, they give no evaluation of knowledge externalities relatively to more traditional agglomeration forces[5].

By examining the choices made by firms to locate their R&D, we intend to evaluate each of these forces and to better estimate the local dimension of knowledge diffusion. The next section lays the theoretical foundations of the paper, by examining the hypothesis of localized knowledge spillovers in geography and growth models. Section 3 details the econometric model. Data and results are presented in section 4 and 5 respectively. The last section summarises the main conclusions.

[5] As noticed by Rosenthal and Strange (2005), the evaluation of agglomeration forces driving firms location is not the subject of a unified literature. They review a series of estimations seeking to evaluate the importance of the various agglomeration forces found in the economic geography theories. But they note that these are separate evaluations as long as each of the studies is only assessing one or two distinct forces at most.

2. R&D lab location: Theoretical background

The innovative activity location issue is the main concern in geography and growth synthesis models (see Baldwin et al. 2003 or Baldwin and Martin, 2005 for a review). These models consider, beside the traditional and industrial sectors usually taken into account in centre-periphery approaches, a specific sector dedicated to the production of innovations[6].

Due to spillovers, the capital stock is constantly growing in this sector (and could be considered as a stock of know-how instead of physical stock)[7]. Each capital unit being associated with a variety, this continuous increase in knowledge stock implies that the number of varieties keeps on growing. In a Dixit-stiglitz framework, this inevitably leads to a falling rate of operating profit per variety. If the building costs of a new unit of knowledge capital are constant, then the capital stock increases until the present value of the expected profit for a new variety is lower than the marginal capital building costs. The increasing number of varieties and therefore growth will come to a halt. So growth can only come from exogenous sources.

In order to go beyond this effect while remaining within the Dixit-Stiglitz framework, the unit cost of innovation production must fall over time. A learning curve is introduced to that effect (like in most of literature on endogenous growth): the marginal cost of making new knowledge decreases as idea production increases. It is therefore assumed that a_I decreases when the cumulative output of the sector dedicated to the production of innovation (marked I) increases due to a learning effect (the experience gained on past innovation improves the efficiency of current innovation).

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[6] We owe the first paper introducing the increasing number of varieties in an endogenous manner in a centre-periphery-type of model to Martin and Ottaviano (1999). They present both a Global Spillover and a Local Spillover version with perfect capital mobility. They do not take the case of purely local or purely global knowledge spillovers into account, though. The intermediate case is studied by Baldwin et al. (2001) in a context of capital immobility.

[7] The perfect competition hypothesis in this sector dedicated to the production of innovation is maintained despite the hypothesis of dynamic scale economies, assuming that each firm of the sector is too small to internalize spillovers.

The learning curve (in the North region) is as follows:

$$F = w_L a_I, \quad a_I \equiv \frac{1}{K^w A}, \quad A \equiv s_K + \lambda(1 - s_K)$$

where λ measures the degree of location of spillovers. The cost function is isomorphic in the South, hence $F^* = w_L / K^w A^*, \quad A^* \equiv \lambda s_K + 1 - s_K$. In both regions, the cost is calculated by the amount of labor a_I needed to produce a knowledge unit, times the salary w_L.

The number of labour units a_I (a_I^* respectively), however, is the inverse function of the quantity of capital produced by all firms in sector I for both regions (K) multiplied by A, which is a function of the share of capital located in the North (s_k).

In a way, λ measures the ease with which public knowledge stock travels. Thus λ=1 means that ideas spread at no cost (spillovers are global), whereas λ=0 means that ideas don't spread (spillovers are only local). For 0<λ<1, one may consider that 1-λ is the fraction of the public knowledge stock which "melts" in transit to the other region.

The way these spillovers are passed on in space is therefore determining in order to understand both the location of economic activities and the impact of this location on long-term growth.

If spillovers are assumed to move perfectly among firms of different regions, the agglomeration forces are weaker and geography has no impact on the long-term growth rate.

In this case, λ=1 so that the learning curve becomes:

$$F = w_L a_I, \quad F^* = w_L^* a_I^*; \quad a_I = a_I^* = 1/K^w, \quad K^w = K + K^*$$

a_I (a_I^* respectively) is the inverse function of the quantity of capital units produced by all firms in sector I in both regions.

If there is no geographical constraint to public knowledge diffusion, firms in the innovative sector benefit from the same amount of spillovers regardless of their location. Then, several equilibria may arise, among which the symmetric one. If transaction costs are high enough, the centre-periphery equilibrium is not stable because the South is encouraged to replace its depreciated capital and innovate. Despite the market being small in the South, it is indeed protected from northern competitors by high transportation costs. Conversely, when these costs are low, this protection decreases and the small size of the southern market prevails. This results in the agglomeration in the North.

In the case of localized spillovers, the centre-periphery equilibrium becomes systematic. Because of local knowledge spillovers, if a region has a small initial advantage, it accumulates experience in the innovative sector faster than the other region. This lowers the replacement cost of capital faster and in turn attracts more resources to the innovative sector of this region. As a consequence, the agglomeration process is strengthened. Moreover, in that case, the location of innovative activities may affect growth. Indeed, if knowledge diffusion between regions[8] is not perfect, the concentration of economic activities in one region reinforces spillover phenomena. Then, the cost of innovation is minimum, which leads to a higher growth rate. On the contrary, in case of symmetric distribution of the industrial and innovative sectors between regions, learning spillovers are as small as possible and the cost of innovation as high as possible[9]. Thus, while maximising learning spillovers and minimising the cost of innovation, a regional disequilibrium raises the economy to a higher growth path benefiting both regions[10].

The implications in terms of public policies are not neutral. In the case of localized spillovers, public intervention in favour of the development of economic activities in poor regions does not only resolve

[8] When trading goods becomes less costly and we go beyond the sustain point, the centre-periphery equilibrium becomes the only stable one.

[9] When the degree of freedom of trade ϕ, is below the break point.

[10] For the peripheral region, there is actually a tension between the static loss due to relocation and the dynamic gain due to the growth take-off. Then if the Centre region has to win, the effect on the periphery is ambiguous. When the share of expenditure on industrial goods is low, the negative static effects are not enough to counterbalance the growth rate increase. Conversely, when the share of expenditure on industrial goods is high enough, dynamic gains prevail and the growth take-off benefits both regions.

the spatial rebalancing issue. It is also a way to increase the global growth level. Validating the assumption of a local dimension of knowledge externalities is therefore a deserving topic. The studies previously carried out to that effect by econometric works in geography of innovation (see Autant-Bernard and Massard 2003 or Audretsch and Feldman 2005 for review) are based on aggregated data and do not allow us to directly assess the λ parameter. Using a location choice model thus appears to be a way to more directly capture the agents' behaviours and their consequences on the agglomeration dynamics of innovative activities.

3. R&D lab location: An econometric model of firm location choice

The method is based on a discrete choice model. This method is quite usual in studies of multinational firm location [11]. However, these works assess the location determinants, no matter what the type of activity may be. Our study differs from these works insofar as it aims at capturing the specific determinants in terms of research activity location. It also differs from previous works by taking the firms' distinctive features into account, beside regional characteristics. Lastly, we introduce spatial dependence in order to test the geographic dimension of knowledge externalities.

An extended conditional logit model of individual choices

Each firm choosing between N potential locations, investors are assumed to select a location if and only if this location gives higher profits than all the others.

Each firm chooses location j if the expected profits, noted Π_j are higher than all the expected profits associated to other locations:

(1) $\Pi_j = \max\{\Pi_k\} \quad with \quad k = 1, \ldots N$ so if $P_j = P(\Pi_j > \Pi_k)$, $\forall k$, with $k \neq j$.

[11] See Mayer and Mucchielli (2004) for a review.

The profits of each firm, associated to location j, are given by:

(2) $\Pi_j = V_j + \varepsilon_j$

where V_j is a function of all the characteristics of area j. ε_j is a random perturbation.

We choose a linear expression for V_j :

(3) $V_j = \beta X_j$

where X_j is the vector of the observable characteristics of location j and β is the vector of the parameters to be estimated.

This conditional logit is extended to control for the individual specificities that may influence the choice of an area[12]. Indeed, the location choice of an SME may differ from the choice made by multinational firms.

Hence the following latent model:

(4) $\Pi_{ij} = X_{ij}\beta + Z_i \gamma_j + \varepsilon_{ij}$

where Z_i are the individual features. Since a unique vector of parameters can't be estimated for these individual variables, one vector of parameter is estimated for each region (γ_j)[13]. This will allow to evaluate, apart from their observed features, which kind of laboratory regions are more likely to attract. In this framework, the spatial dimension of knowledge spillovers may be measured by introducing spatial dependence.

[12] Such individual data are not observed in models of multinational firm location.

[13] The probability for firm *i* to locate its R&D lab in location j is thus given by:

$$P_j = \Pr ob(y_i = j) = \frac{\exp(X_{ij}\beta + Z_i \gamma_j)}{\sum_{k=0}^{N} \exp(X_{ik}\beta + Z_i \gamma_k)}, \quad \forall k \neq j$$

Discrete choice models and spatial dependence

As Flemming (2004) points out, the study of spatial dependence in discrete choice models has received little attention in literature. The very few studies that have applied spatial econometric techniques to models with discrete dependent variables focus on binary choices.

Case (1992) applies a variance analysing transformation in maximum likelihood estimator to analyse the decisions by farmers to adopt new technologies. Marsh, Mittelhammer and Huffaker (2000), also applied this approach to correct spatial autocorrelation in a probit model with geographic regions while examining a data set pertaining to disease management in agriculture. Murdoch, Sandler and Vijverberg (2003) study the adoptions of environmental treaties by European countries using the RIS simulator developed by Beron and Vijverberg (2004). Extending Case's spatial probit by allowing spatial dependence to vary across regions, Coughlin, Garret and Hernandez-Murillo (2004) differentiate states with a lottery from those without a lottery. The most promising issue probably relies on Bayesian econometrics (LeSage, 1997). Holloway, Shankar and Rahman (2002) use Bayesian tools to estimate a spatial probit with a binary dependent variable. However, the extension to the multinomial case requires further research[14].

As a consequence, the simplest way to account for the spatial dimension is to introduce spatially lagged explanatory variables[15]. The spatial dimension of knowledge spillovers is introduced as follows:

(5) $$\Pi_{ij} = WX_j \lambda + X_j \beta + Z_i \gamma_j + \varepsilon_{ij}$$

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[14] Using these Bayesian econometric tools, Bolduc, Fortin and Gordon (1997) do estimate a multinomial probit model. However, the spatial dimension is introduced at the expense of the covariance matrix specification. Indeed, they assume that the perturbation covariance matrix is diagonal (instead of the bloc-diagonal matrix which usually characterises multinomial probit models). In other words, they do not account for the correlation that occurs between the random perturbations for a same individual.

[15] A similar approach is used by Nelson et al. (2004) to test the impact of transport infrastructures on the deforestation in developing countries.

where W is a contiguity matrix. The latent variable is a function of the regional explanatory variables values at neighbours[16].

Estimations of this model will allow to evaluate the relative importance of the main factors governing the choice of one location. Moreover, the introduction of spatial dependence allows to test whether a spatial diffusion of knowledge spillovers occurs. The significance of λ will indicate whether R&D lab location choices are sensitive to the internal characteristics of the area only, or if they also depend on the characteristics of the neighbouring areas. As mentioned above, this parameter is of key importance in the models of the geography and growth synthesis. If $\lambda=0$, spillovers are geographically bounded. A region with a small initial advantage accumulates experience in the innovative sector faster than the other region. The cost of innovation in this region decreases more rapidly, and more resources are devoted to the innovative sector of this region. Then, geography affects growth (Martin and Ottaviano, 1999, Baldwin et al., 2001). While maximising learning spillovers and minimising the cost of innovation, a centre-periphery configuration may raise the economy to a higher growth path. Conversely, if $\lambda=1$, firms can benefit from knowledge spillovers, regardless of their location. Then, geography does not affect growth.

4. Data

The sample comes from an original database computed from the "2001 R&D Survey" and the "2001 Firms Survey" (of the French R&D Ministry and the French Industry Ministry respectively). The R&D survey focuses on all the firms (having more than 20 employees) which carry out some R&D and employ at least one full-time researcher. The location (region and department) is subjected to a systematic coding. The Firm Survey gives the main characteristics of the firms having more than 20 employees (sales, investments, employees, etc.) and the location of each plant.

[16] Since no spatial dependence is introduced in the error term, we not account for the heteroskedasticity and the endogeneity induced by spatial dependence. As we will mention at the end of this paper, this is largely insufficient. However, it gives a first approximation of the spatial dependence effect between regions and its impact on R&D lab location.

Among the 22,000 industrial firms observed in the "Firms Survey", a sample of 1,689 innovative firms has been identified in the R&D survey, with a total of 2,024 decisions of R&D location. The two databases give located information about these firms and their R&D laboratories and concerning the main features of their locations. The geographical unit is the administrative French Region (NUTS 2).

At the firm level, several characteristics may affect the location choice. First of all, the decision process may differ according to the size of the R&D plant. On the one hand, the decision-making process itself is probably not identical for large research laboratories and small units. On the other hand, the ability to benefit from externalities, and therefore the degree of sensibility to the characteristics of the industrial and technological environment is likely to vary according to the size of the research unit. This size can be approximated by the R&D expenditure. The latter is collected in the R&D survey. These data are not directly observed at the plant level, but they are localized. Indeed, each firm has to mention the share of R&D carried out in each of its implantations. This allows us to introduce a variable (RD) accounting for the local R&D expenditure of each firm.

Secondly, industry-specific features can also lead to different location choices. Knowledge production and diffusion processes may differ significantly between industries. The determinants of location choices and of spatial constraint in particular are not necessarily the same for every sector. In order to account for this effect, we observe the industrial field of research within which each R&D unit carries out research (19 sub-sectors are distinguished).

In addition to these effects which are specific to research units, some of the characteristics of the firms to which they belong might influence location choices. Works on multinational firm location show for instance that foreign companies don't behave in the same way as national companies when it comes to choosing their location. Their much less acute knowledge of the country leads them to overlook secondary locations. In order to test whether the location strategy of foreign companies differs significantly from the one of French firms, we use a dummy variable indicating whether the firm belongs to a foreign company (FORCO).

Finally, an important characteristic likely to substantially affect the decision made by firms regarding where to locate their R&D relies on the location of their production. Indeed, feedback between production and research activities as well as research on controlling transportation costs between sites justify locating research units near the production units of the company. The study carried out by Kenney and Florida (1994) on the organization and location of biotechnology R&D activities in Japan show that applied research and production engineering need to be located near the production site. Unfortunately, our data set does not allow to get such a piece of information. As an approximation of this effect, we introduce a dummy variable for firms with only one plant (SINGPL). Indeed, in this case, the choice of R&D location is probably largely driven by the location of production.

At the regional level, the main forces at work, underlined in the geography and growth models, have been discussed in the previous section: circular causality, competition, knowledge spillovers. The total number of workers (EFFREG) in the industry is used to account for the agglomeration forces due to circular causality. The production of the other innovative firms of the region (CAREG) measures the dispersion force produced by local competitors.

The global level of spillovers is accounted for by the following variables:

- The private R&D expenditures of the other labs settled in the area, in the same industry as firm *i* (noted RDREG). Patents, frequently used in the literature to measure a stock of knowledge should have been used instead of R&D expenditure. However, they are not the most relevant indicator in this case. By definition, patents reflect codified knowledge, whereas the hypothesis of a local dimension of knowledge spillovers is based on its tacit nature.

- The level of knowledge production from public labs, measured by the number of scientific publications in the related fields of firm *i* (noted PUBREG). Publications are used instead of public expenditure, because the latter are not available at a regional scale in France. For each publication, the location of the author is known. However, there can be many authors, not necessarily localized in the same region. In that case, a fractional counting is used, depending on the number of co-authors. The database is computed by the French « Observatoire des Sciences et Techniques » from the information of the Science Citation Index of 1995, 1996 and 1997. Publications are filed into 8 scientific fields. Thanks to the OST report that details each scientific field, we built the concordance with the private research classification (see Table A1 in the appendix).

Hence the full latent model:

$$
\begin{aligned}
&\Pi_{ij} = \beta_0 + \beta_1 RDREG_j + \beta_2 PUBREG_j + \beta_3 EFFREG_j + \beta_4 CAREG_j + \\
(6)\qquad &\lambda_1 W.RDREG_j + \lambda_2 W.PUBREG_j + \lambda_3 W.EFFREG_j + \lambda_4 W.CAREG_j + \\
&\gamma_{1j} RD_i + +\gamma_{2j} FORCO_i + +\gamma_{3j} SINGPL_i + \varepsilon_{ij}
\end{aligned}
$$

Data are expressed in logarithms. The regional variables are smoothed other three years to account for the cumulative feature of knowledge and avoid erratic variations associated with data collection.

W is the first order contiguity matrix, with row standardization. Then, each spatially lagged explanatory variable can be interpreted as the mean of this variable for the neighbours of region j. The results appear quite robust to this specification since the inverse distance matrix as well as the two nearest neighbours' matrix do not give very different results.

The main features of these data are given in the appendix. Except in few industries like aerospace, energy or computer, R&D labs are present in almost all regions. However, data exhibit a strong polarisation of R&D. Two regions concentrate more than 37% of R&D plants: the Paris region (Ile de France) and Rhône-Alpes, with 427 and 328 labs respectively. Only two other regions (Centre and Pays de la Loire) have more than one hundred R&D plants. This spatial concentration is particularly high in the computer and the pharmaceutical industries that localise 40% of their R&D labs in Ile de France. Maps 1 to 3 show that the geographical distribution of R&D laboratories is approximately the same as for R&D and public research expenses. The spatial organization of the latter is slightly different, though. The third French région is not Centre, which actually counts very little public research, but the PACA région (Provence-Alpes-Côte d'Azur). This difference also leads us to believe that the régions accommodate laboratories of various sizes. The French région Centre, although second in the number of laboratories, is only third when we measure R&D expenses. It therefore accommodates small research units on average.

The sectoral repartition is also characterized by a high level of concentration. 30% of R&D labs concern the Machinery and Equipment industry or Chemistry (with 341 and 260 plants respectively). These sectoral disparities cannot be taken into consideration using dummy variables. Since some industries do not have R&D labs in each region, we cannot estimate a vector of parameters for each region. However, these sectoral effects are partly accounted for by the individual features of each plant. The size of R&D labs, the importance of foreign groups and single plant firms are for a large part specific to each industry.

In order to observe how these individual features impact the location decision, the next point present the results obtained from the regional variables only. Then, these results are compared to those obtained when adding individual features.

5. Results

Regional determinants of R&D lab location

A first set of estimations introduces only regional characteristics. Three models are estimated (results are reported in table 1). The first model includes only variables relative to the local characteristics. Results from this model confirm the observations of previous studies on aggregated data: the positive impact of private and public research carried out locally. Both RDREG and PUBREG have positive and significant coefficients. This agglomeration effect resulting from knowledge spillovers reinforces the more traditional agglomeration forces measured by the number of workers in the area (EFFREG). The dispersion effect resulting from competition between firms, and measured by the production of local innovative firms (CAREG), seems validated. A relatively high level of R&D carried out locally by other firms raises the probability that a firm chooses to locate its R&D in one region, while a relatively high level of production of the latter tends to reduce the settlement probability.

In order to evaluate the spatial dimension of knowledge spillovers, the second specification introduces the spatially lagged R&D. This variable has a positive and significant impact on the location choices. With a value of 0.06, the estimated coefficient is smaller than the coefficient obtained for the regional R&D (0.23), supporting the hypothesis of a decline of knowledge diffusion over space.

This positive effect is not observed for public R&D. This appears as a French specificity. Indeed, Anselin, Varga and Acs (1997) find that in the U.S., public research has a broader geographical spread than private R&D. This finding is a persistent one on French data. Autant-Bernard (2001) and Autant-Bernard and Massard (2005) even observe some “shadow effects”. Public research is highly concentrated in Paris and knowledge diffusion through space is hardly achieved.

However, as public and private R&D are the only spatially lagged variable, they can reflect all the effects due to other characteristics of surrounding regions. For this reason, the third model includes all the spatially lagged explanatory variables.

The results confirm the presence of intraregional knowledge spillovers (see column 3 of table 1). Once accounting for traditional agglomeration and dispersion effects, the coefficient associated to W-RDREG is higher and still significant.

As assumed in economic geography model, circular causality due to more traditional agglomeration effects seems geographically bounded. A negative effect appears due to the proximity to large regions. No competition effect is observed from the surrounding regions (W-CAREG is not significant) and positive effect result from neighbouring agglomeration. On the contrary, the size of the surrounding regions (measured by the variable W-EFFREG) has a negative and significant coefficient. Regions located close to large metropolitan areas suffer a loss of attractiveness. The cumulative effects associated to large region seem to increase their attractiveness at the expense of the peripheral regions. This negative effect is partly counterbalance by interregional knowledge diffusion.

[Insert table 1]

Regional and individual determinants of R&D lab location

The second set of estimations introduces, together with the regional variables, the individual characteristics of the R&D lab and of the firm to which it belongs. This improves the explanatory power of the model[17], with a small increase of the adjusted R^2. The results are reported separately for regional determinants and individual determinants. Table 2 highlights the impact of regional characteristics once accounted for individual features, while the estimated coefficients for individual characteristics are reported in table 3.

Most of the results reported in table 2 are similar to those presented in table 1. Location choices are positively and significantly influenced by private R&D carried out inside regions as well as by more traditional agglomeration and dispersion forces.

However, the introduction of the individual variables modifies the sign of the PUBREG parameter. Once controlled for individual features driving location choices, the presence of a large amount of

[17] The small values for the goodness of fit indicate that the location models such as the one we develop here have to be considered cautiously. The location process is supposed to result from a rational decision made by firms to maximise their profits. However, some recent studies on firm location strategy highlight spatial inertia, mimetism and networks of relationships are probably much more decisive than the characteristics of the location themselves.

public research in the area seems to reduce the attractiveness of the region[18]. This result may come from differences in the spatial organisation of private and public research. French public research has a very high level of concentration. Then, private R&D labs appear to be relatively dispersed compared to public research. This negative association may also confirm the idea of the importance of an absorptive capability to benefit from public research (Cockburn and Henderson, 1998). As noticed below, the introduction of individual variables highlights that large R&D labs are more likely to be located in the largest areas, where public research is concentrated. For small firms, relationships with public research are thinner. Since they would not benefit from public research, the dispersion forces associated to large agglomerations would incite small R&D labs to locate outside the areas with lots of scientific publications[19].

This result does not mean that public research does not benefit to private R&D labs, but that these spillovers do not rely on geographic proximity[20]. This is confirmed by the estimations reported in column 3 where no spatial dependence is observed for public research. However, we cannot rule out the fact that the measure of public research, through the number of publications, may be an imperfect indicator of the research effort and its impact on private research. Indeed, it does seem unlikely for crowding-out effects on the labour market for instance to prevail over traditionally expected knock-on effects of public research. Moreover, the regional scale may be too large to account for those public spillovers. Previous studies based on a smaller geographic scale observe that public research does produce a positive impact in the close neighbourhood whereas no positive effect appears at a larger distance (Autant-Bernard and Massard, 2004, Anselin, Varga, Acs, 1997[21]). In the French case, Autant-Bernard and Massard (2004) also highlight that shadow effects may appear. Public research carried out

[18] Using aggregated data, the models based on a knowledge production function cannot control for individual effects and conclude to a positive impact of public research on innovation. The result we obtain here invites us to consider cautiously the observation drawn from aggregated data.

[19] Varga (1998) obtained similar results for the U.S. on aggregated data. A critical mass of private R&D must be reached to observe a local effect from public R&D spending. However this point should be studied more deeply. It is inconsistent with Beise and Stahl's results, for which small firms are more likely to establish local relations with public research centres (Beise and Stahl, 1999). Audretsch and Vivarelli (1994), also observed that small firms benefit more from academic research than large firms.

[20] Public research may also produce a local effect indirectly by inducing private R&D spending (Jaffe, 1989).

[21] Using NUTS 3 data, Autant-Bernard and Massard (2004) observe that the positive impact of French public research is limited within small areas ("departments"). They find no evidence of spillovers effects for public research between contiguous "departments". Similar results are obtained by Anselin, Varga and Acs (1997) in the American case where no spillover effect occurs beyond a 75-mile neighbourhood.

at a distance (eg. the second order contiguity level) has a negative impact on local innovation[22]. This shadow effect could explain the negative sign observed here since we consider a large territorial scale.

Concerning the spatial dependence process, the introduction of individual features slightly modifies previous results. Traditional agglomeration and dispersion effects (measured by EFFREG and CAREG) seem geographically bounded. The parameter associated to W-EFFREG is still negative but no longer significant. However, the spatially lagged R&D remains significant with a smaller coefficient than RDREG. Thus, the location decision does not only depend on the internal characteristics of the region. It is driven by the knowledge spillovers available in the neighbouring areas also. The spatial parameter is three times as small as the coefficient of internal R&D, supporting the hypothesis of a local dimension of knowledge spillovers.

[Insert table 2]

Table 3 gives the estimated coefficients associated to firms and R&D labs characteristics. These effects are evaluated relatively to the reference region (PACA). The results obtained for the three specifications are reported. They lead to very similar conclusions.

First, not surprisingly, when they belong to foreign companies, firms are more likely to locate their R&D in frontier regions (Nord-picardie, Haute-Normandie, Alsace-Lorraine, Champagne-Ardennes) as well as in the main industrial regions (Rhône-Alpes and Ile de France).

Second, the attractiveness of an area seems to differ according to the size of the R&D plant. The higher the R&D expenditure, the higher the probability to locate in agglomerated areas[23]. Indeed, regions with a positive and significant coefficient for R&D plant expenditure (RD) are Ile de France and Rhône-Alpes. Both concentrate the major part of French economic activities and all the more the major part

[22] The shadow effect in public research observed by Autant-Bernard and Massard (2004) for the extended neighbourhood appears to be a French specificity since no similar result appears in the American case.

[23] Since the coefficients are estimated relatively to the reference region, this means that higher regions than PACA are more likely to attract large R&D plants. The same interpretation holds for foreign companies.

of innovative activities (respectively 30% and 9% of the French GDP, and 48% and 12% of R&D expenditure).

Conversely, single plant firms have got a higher propensity to settle and develop R&D activities in relatively more peripheral regions. Their location is probably more influenced by the factors underlying the location of production. In that case, the competitive effect between productive structures may overbalance the attraction effect induced by knowledge spillovers.

[Insert table 3]

6. Conclusion

Looking at 2024 decisions of R&D lab location in France, this paper intends to better understand the mechanisms underlying the geography of innovation. A conditional logit is implemented to evaluate the relative importance of the main factors driving the location choice. Estimations indicate that traditional agglomeration effects are reinforced by centripetal forces induced by knowledge spillovers stemming from private research. Estimations also confirm the local dimension of spillovers. The profit associated to the location in one region is primarily affected by the relative amount of knowledge available in this region, and to a lesser extent, by the relative amount of knowledge available in neighbouring areas. On the contrary, a low level of academic research in the target region increases the probability of setting up R&D labs.

These results have important implications in terms of technological policy, especially in the European context dominated by the tension between regional equity and the building of technological poles of worldwide influence. First, according to our results, policy makers should enhance the attractiveness of their region by developing the complementarities of private R&D activities within the region but also with neighbouring regions. Public investments in local scientific research do not appear as the most efficient way to reach this regional target. However, our study does not take other issues into account for policy makers. We have to carry on further research to explore the efficiency of other potential actions likely to favour the settlement and the development of R&D labs (such as institutions of technology transfers, infrastructures of communication, etc).

Second, our results open up another interesting issue for policy makers. Our study accounts for firm specific characteristics underlying R&D location choices. Foreign companies, large R&D labs or single plant firms are not attracted by the same local features. This is of particular importance for regions. Their attractiveness differs according to the individual characteristics of firms. Being aware of the regional forces would help regional policy makers to target which kind of R&D labs to attract. Obviously, our results remain very rough on this point, but they constitute a first step for further research.

Finally, the way spatial dependence is accounted for needs to be improved. Spatial spillovers are assumed to be 'local' in the sense of Anselin's classification (Anselin, 2003). Yet, the uncertainty affecting the probability that a firm locates its R&D in one region depends on the unobservable characteristics of this region (image, climate for instance). But these characteristics are likely to affect also neighbouring areas. Consequently, spatial autocorrelation is probably not entirely accounted for by the spatially lagged explanatory variables and spatial dependence can appear in the random perturbation. If that is the case, the estimated coefficients remain unbiased but are no longer efficient[24]. Moreover, we do not account for the endogeneity resulting from the bi-directional dimension of spatial dependence. If knowledge spillovers are not bounded inside regions, the profit associated with the location in one region depends positively on the profit that can be expected in a neighbouring region, and vice versa[25]. Thus, a natural extension of these results relies on a true consideration of the spatial dependence process, by introducing the spatially lagged dependent variable and allowing for spatial

[24] The maximum likelihood estimator gives efficient estimates for spatial models with continuous dependent variable. However, if not corrected for, spatial dependence in discrete choice models induces heteroskedasticity and the parameters estimated by the maximum likelihood are inefficient (Fleming, 2004).

[25] Then, estimated parameters are both biased and inefficient (Le Gallo, 2002).

errors. We need to carry out further research to find a proper way to implement a spatial multinomial model. This implies extending the spatial probit model to the multinomial case. This will allow us to consider the decision of setting up and developing R&D labs as an endogenous variable.

Acknowledgement: I am grateful to Henri Overman, Olivier Parent and participants at Kiel Spatial Econometric Workshop and GDR ASPE for their helpful comments and discussions. I am especially indebted to Vernon Henderson for his suggestions and encouragement at the source of this project. Thanks also to my colleagues of the French ministries of industry and research and the OST for collecting the data as well as to Lise Cause and François Martin for their kind assistance.

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Table 1: Regional determinants of R&D lab location

	Model 1	Model 2	Model 3
RDREG	0.231***	0.228***	0.233***
	(8.978)	(8.669)	(8.826)
PUBREG	0.063**	0.086***	0.071**
	(2.477)	(2.943)	(2.349)
EFFREG	0.669***	0.671***	0.690***
	(14.103)	(14.034)	(14.328)
CAREG	-0.077***	-0.079***	-0.084***
	(-7.576)	(-7.747)	(-8.077)
W-RDREG		0.055**	0.133***
	-	(2.093)	(3.112)
W-PUBREG		0.017	0.024
	-	(0.420)	(0.570)
W-EFFREG			-0.171**
	-	-	(-2.406)
W-CAREG			-0.020
	-	-	(-0.705)
Individual features (see table 3)	No	No	No
McFadden R^2	0.144	0.145	0.145
Adjusted-R^2	0.144	0.145	0.145
Obs.	2024	2024	2024

The figures between brackets are t ratios.

*Significance thresholds are indicated by *, ** and *** which signify 10%, 5% and 1%, respectively.*

Table 2: Regional determinants of R&D lab location

	Model 1	Model 2	Model 3
RDREG	0.250***	0.257***	0.258***
	(8.919)	(9.040)	(9.051)
PUBREG	-0.187**	-0.182**	-0.181**
	(-2.411)	(-2.005)	(-1.997)
EFFREG	0.537***	0.535***	0.539***
	(9.750)	(9.740)	(9.732)
CAREG	-0.093***	-0.098***	-0.099***
	(-8.662)	(-8.991)	(-8.979)
W-RDREG		0.075**	0.095**
	-	(2.505)	(2.012)
W-PUBREG		-0.032	-0.022
	-	(-0.216)	(-0.148)
W-EFFREG			-0.060
	-	-	(-0.699)
W-CAREG			-0.002
	-	-	(-0.071)
Individual features (see table 3)	Yes	Yes	Yes
McFadden R^2	0.160	0.161	0.161
Adjusted-R^2	0.159	0.159	0.159
Obs.	2024	2024	2024

The figures between brackets are t ratios.

*Significance thresholds are indicated by *, ** and *** which signify 10%, 5% and 1%, respectively*

Table 3: Individual determinants of R&D lab location by region

REGIONS	SINGLE PLANT (SINGPL)			FOREIGN COMPANIES (FORCO)			R&D EXPENDITURE (RD)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Ilede France	0.090 (0.307)	0.093 (0.313)	0.088 (0.298)	0.613* (1.824)	0.618* (1.835)	0.618* (1.837)	0.107*** (4.041)	0.111*** (2.814)	0.112*** (2.822)
Champagne-Ardennes	0.467 (1.220)	0.483 (1.260)	0.480 (1.251)	1.048** (2.417)	1.048** (2.417)	1.046** (2.413)	-0.064 (-1.550)	-0.060 (-1.383)	-0.059 (-1.354)
Picardie	-0.144 (-0.392)	-0.132 (-0.358)	-0.137 (-0.372)	1.054*** (2.709)	1.052*** (2.702)	1.049*** (2.693)	-0.039 (-1.131)	-0.036 (-1.008)	-0.034 (-0.951)
Haute Normandie	0.143 (0.392)	0.154 (0.420)	0.151 (0.411)	0.879** (2.197)	0.881** (2.202)	0.880** (2.198)	-0.044 (-1.309)	-0.044 (-1.254)	-0.042 (-1.206)
Centre	0.198 (0.594)	0.209 (0.623)	0.203 (0.605)	1.264*** (3.409)	1.272*** (3.427)	1.269*** (3.418)	-0.035 (-1.093)	-0.032 (-0.870)	-0.032 (-0.868)
Basse Normandie	0.132 (0.281)	0.135 (0.386)	0.134 (0.283)	0.335 (0.614)	0.338 (0.620)	0.334 (0.612)	-0.093** (-2.193)	-0.088 (-1.563)	-0.085 (-1.502)
Bourgogne	0.499 (1.410)	0.503 (1.420)	0.502 (1.416)	0.670 (1.624)	0.674 (1.634)	0.674 (1.632)	-0.041 (-1.209)	-0.041 (-1.153)	-0.040 (-1.113)
Nord-Pas-de-Calais	0.929*** (2.782)	0.916*** (2.676)	0.911*** (2.662)	0.667* (1.661)	0.655 (1.630)	0.651 (1.619)	-0.052* (-1.657)	-0.045 (-0.767)	-0.042 (-0.722)
Lorraine	0.943*** (2.662)	0.943*** (2.632)	0.940*** (2.624)	1.182*** (2.868)	1.177*** (2.853)	1.173*** (2.844)	-0.073** (-2.129)	-0.058 (-1.215)	-0.056 (-1.168)
Alsace	1.243*** (3.678)	1.257*** (3.682)	1.259*** (3.687)	1.614*** (4.117)	1.612*** (4.110)	1.608*** (4.098)	-0.112*** (-3.276)	-0.098*** (-2.150)	-0.098** (-2.139)
Franche-Comté	0.586 (1.536)	0.598 (1.560)	0.597 (1.559)	0.342 (0.735)	0.357 (0.767)	0.356 (0.764)	-0.062 (-1.626)	-0.055 (-1.245)	-0.053 (-1.199)
Pays-de-Loire	0.546* (1.681)	0.551* (1.671)	0.545* (1.652)	0.623 (1.612)	0.621 (1.605)	0.617 (1.594)	-0.004 (-0.124)	0.005 (0.117)	0.006 (0.138)
Bretagne	0.706** (1.975)	0.715** (1.979)	0.714** (1.977)	-0.085 (-0.182)	-0.060 (-0.128)	-0.064 (-0.138)	-0.034 (-1.107)	-0.024 (-0.529)	-0.021 (-0.463)
Poitou-Charentes	0.145 (0.331)	0.146 (0.330)	0.142 (0.320)	0.303 (0.589)	0.311 (0.604)	0.305 (0.592)	-0.056 (-1.430)	-0.049 (-0.872)	-0.047 (-0.837)
Acquitaine	0.634* (1.767)	0.649* (1.792)	0.634* (1.747)	0.554 (1.289)	0.568 (1.320)	0.550 (1.277)	-0.035 (-1.174)	-0.023 (-0.544)	-0.024 (-0.567)
Midi-Pyrénées	0.484 (1.351)	0.514 (1.363)	0.499 (1.374)	0.219 (0.492)	0.244 (0.548)	0.234 (0.525)	-0.004 (-0.148)	0.006 (0.158)	0.004 (0.107)
Limousin	0.516 (1.062)	0.521 (1.065)	0.513 (1.047)	0.432 (0.716)	0.444 (0.735)	0.439 (0.727)	-0.079 (-1.574)	-0.071 (-1.126)	-0.072 (-1.129)
Rhône-Alpes	0.681** (2.341)	0.704** (2.403)	0.697** (2.375)	0.726** (2.119)	0.737** (2.151)	0.733** (2.138)	0.072*** (2.996)	0.080*** (2.636)	0.078*** (2.545)
Auvergne	0.511 (1.140)	0.523 (1.163)	0.520 (1.156)	0.419 (0.741)	0.419 (0.740)	0.417 (0.737)	-0.132*** (-2.931)	-0.126*** (-2.448)	-0.125*** (-2.435)
Languedoc-Roussillon	0.664 (1.532)	0.671 (1.547)	0.667 (1.537)	-0.047 (-0.081)	-0.036 (-0.061)	-0.038 (-0.065)	-0.028 (-0.707)	-0.027 (-0.654)	-0.027 (-0.652)

The figures between brackets are t ratios.
*Significance thresholds are indicated by *, ** and *** which signify 10%, 5% and 1%, respectively.*

APPENDIX:

Table A1: Relations between industries and scientific fields

INDUSTRIES	SCIENTIFIC FIELDS
Machines and equipment	Physical sciences and engineering
Chemistry	Chemistry
Instrumentation	Physical sciences and engineering
Radio, TV, com. equipments	Physical sciences and engineering
Electricity	Physical sciences and engineering
Pharmaceuticals	Basic biology, Medical research
Work on metals	Physical sciences and engineering
Rubber, plastics	Applied biology, Chemistry, Physical sciences, Engineering
Car	Physical science and engineering
Textile, clothes	Applied biology, Chemistry
Other mining and metallurgy	Chemistry, Univers sciences, Engineering
Aerospace	Univers sciences, Engineering
Building material and ceramic	Chemistry, Physical sciences, Engineering
Wood, paper, cardboard	Applied biology, Chemistry, engineering
Shipbuilding	Engineering
Energy (including mining)	Physical sciences, Univers sciences, Engineering
Office machines and computer	Physical sciences and engineering
Glass	Chemistry, Physical sciences and engineering
Other industries (building, civil engineering, transportation and communication)	Engineering

Table A2: Definition of variables

Variable	Definition
RDREG	Private R&D expenditures of the other labs settled in the area, in the same industry as firm *i*
PUBREG	Number of scientific publications in the region, in the related fields of firm *i*
EFFREG	Total number of workers in the region, in the same industry as firm *i*
CAREG	Sales of the other innovative firms of the region, in the same industry as firm *i*
W-RDREG	Private R&D expenditures of the labs settled in the neighbouring regions, in the same industry as firm *i*
W-PUBREG	Number of scientific publications in the neighbouring regions, in the related fields of firm *i*
W-EFFREG	Total number of workers in the neighbouring regions, in the same industry as firm *i*
W-CAREG	Sales of the innovative firms of the neighbouring regions, in the same industry as firm *i*
RD	R&D expenditures carried out by the firm in each of its locations
FORCO	Dummy variable indicating if the firm belongs to a foreign company
SINGPL	Dummy variable for firms with only one plant

Table A2: Number of R&D plants by regions

REGION	Number of plants
Ile-de-France	432
Rhône-Alpes	330
Centre	125
Pays de la Loire	120
Nord-Pas-de-Calais	94
Alsace	90
Picardie	89
Haute-Normandie	78
Bourgogne	74
Midi-Pyrénées	71
Aquitaine	68
PACA	68
Lorraine	67
Bretagne	64
Champagne-Ardenne	55
Franche-Comté	55
Poitou-Charentes	38
Languedoc-Roussillon	34
Auvergne	30
Basse-Normandie	29
Limousin	26

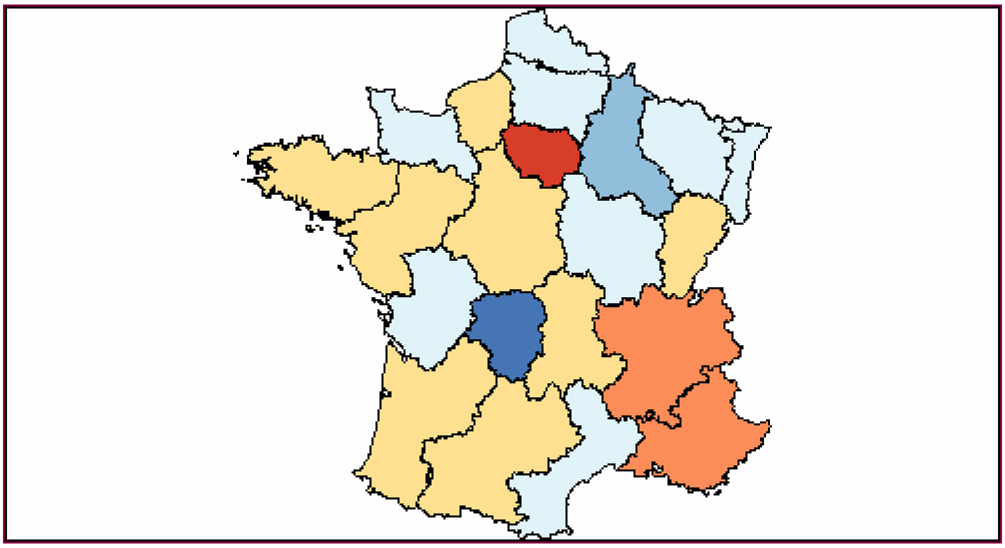
Table A3: Number of R&D plants by industry

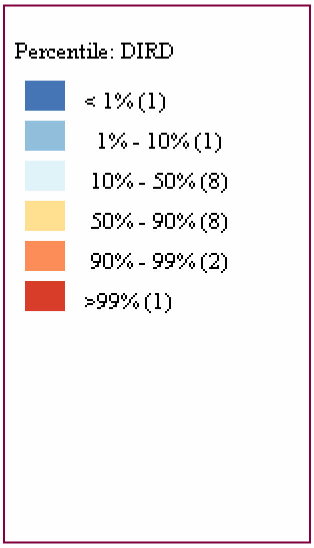
INDUSTRY	Number of plants
Machines and equipment	341
Chemistry	260
Instrumentation	198
Radio, TV, com. equipments	151
Electricity	147
Pharmaceuticals	138
Work on metals	130
Rubber, plastics	123
Car	97
Textile, clothes	82
Other mining and metallurgy	65
Other industries	49
Aerospace	49
Building material and ceramic	44
Wood, paper, cardboard	42
Shipbuilding	30
Energy (including mining)	29
Office machines and computer	29
Glass	21

Table A4: Number of regions with R&D plants by industries

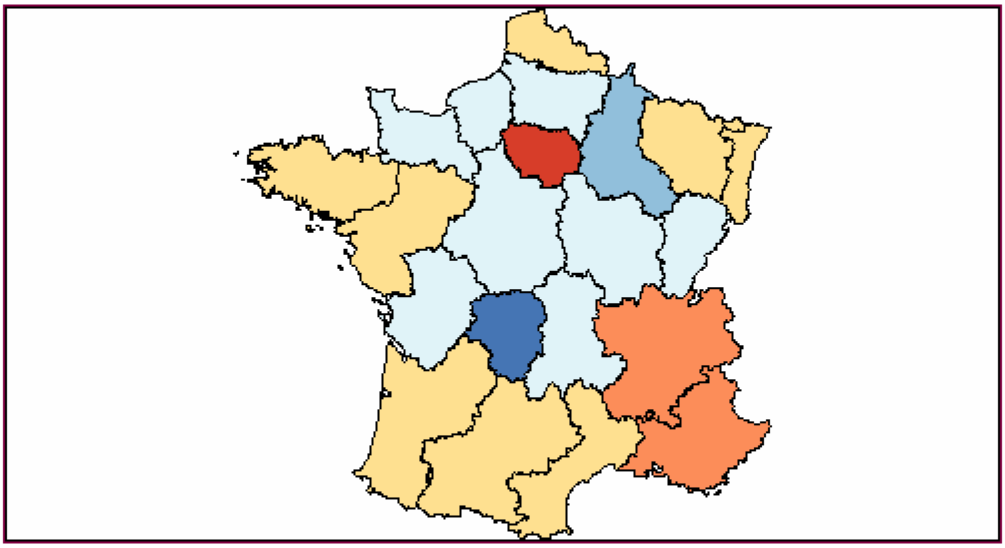
INDUSTRY	Number of regions
Electricity	21
Machines and Equipments	21
Work on metals	21
Rubber, plastics	21
Chemistry	21
Instrumentation	20
Radio, TV and com. equipements	20
Other mining and metallurgy	20
Pharmaceuticals	19
Textile, clothes	19
Car	17
Other industries	17
Wood, paper, cardboard	17
Shipbuilding and other transports	16
Building material and ceramic	15
Aerospace	11
Glass	11
Energy (including mining)	11
Office machines and computer	8

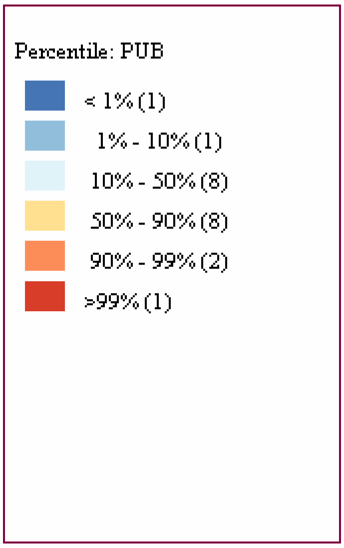
Map 1: R&D expenditure by region





Map 2: Scientific publications by region





Map 3: R&D plants by region